The Connection Between Systems of Government & Economic Prosperity

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Abstract

This paper explores the relationship between democracy and economic prosperity across the world. We use data from the EIU Democracy Index as a benchmark for each country's level of democracy, and the World Bank's Gross Domestic Product (GDP) per Capita Index as a measure of wealth. Additionally, we include each country's average inflation over the past ten years, foreign direct investment (FDI), Gini coefficient, savings as a percent of gross national income, and unemployment rate as secondary explanatory variables to help determine the underlying relationship. A positive correlation between EIU Democracy Index levels and GDP per capita is hypothesized, which is supported by the regression analysis performed.

I. Introduction

In 1977, twenty-four percent of countries qualified as democracies. Forty years later, that number had risen to fifty-seven percent, with over one third of all newly formed nations since 1989 becoming democracies.[1] While the democratization of these countries was driven by a variety of social and political factors, economic concerns also played a significant role. For instance, the collapse of the U.S.S.R. was largely induced by the poor performance of the Soviet economy, even after the numerous reforms of *perestroika*. Following the Soviet Union's disbandment, former Soviet states that embraced a democratic government, such as Estonia and Lithuania, have seen dramatic growth. According to the World Bank, Estonia's GDP per capita has grown by almost 20,000 USD over the past twenty years, while Lithuania's has grown by over 16,000 USD in the same period.[2] This is just one example of countries experiencing a long period of economic growth following their transition to a democracy, and suggests that there might be a link between GDP and system of government.

Nevertheless, previously communist East Asian countries like China and Vietnam have embraced a market economy without fully democratizing and also seen an explosion in economic growth. In 1990, China's GDP per capita was a mere 318 USD, according to the World Bank. As of 2019, this value had soared to over 10,000 USD, an increase of over 3000%.[3] Similarly, Vietnam's GDP per capita grew by 2800% over the same time period.[4] This raises an important question: are these two countries simply outliers, or is there no link between democracy and economic prosperity?

This paper will explore the relationship between a nation's level of democracy and its economic prosperity by using cross-sectional data from the World Bank and the Economist Intelligence Unit (EIU) to create both simple and multiple linear regression models. The primary explanatory variable studied will be the EIU Democracy Index score, and the dependent variable will be GDP per capita. Furthermore, we will include numerous secondary explanatory variables in our analysis to reduce omitted variable bias. We hypothesize that there will be a positive correlation between the EIU Democracy Index score of a country and its GDP per capita. The economic rationale behind this hypothesis is that countries that are more democratic tend to support more of a free market economy,

[1] Pew Research Institute
[2] World Bank GDP per Capita Index
[3] World Bank GDP per Capita Index
[4] World Bank GDP per Capita Index

while those that are less democratic may not. Because a free market is the most efficient type of economy in the long run, this should imply a positive correlation between level of democracy and GDP per capita.

II. Literature Review

Concerning economic journal papers on this subject, there is no clear consensus on the correlation between the level of democracy and GDP per capita of a nation. In fact, there is a sizable amount of research supporting both sides of the argument. Acemoglu et al. (2008) researched the relationship between the Freedom House Political Rights Index and the Polity IV Dataset, two measures of how democratic a country is, and GDP per capita across 150 countries. They considered two time periods: one spanning the years 1970 to 1995, and another spanning the years 1900 to 2000. For the first time period, Acemoglu et al. relied on the Freedom House Political Rights Index data to measure the level of democracy in their sample countries, while in the second time period, they used the Polity IV Dataset. Performing simple regression on both datasets, they found that there was a strong positive correlation between the change in the level of democracy and the logarithm of the change in the GDP per capita of a country. However, after controlling for numerous fixed effects, such as population, savings rate, and trade-weighted GDP, they performed multiple linear regression and found almost no correlation between these two variables.

Heshmati & Kim (2017) explored the relationship between economic growth and democracy using the same Freedom House and Polity IV datasets as Acemoglu et al. but came to a much different conclusion. Instead of taking the raw data values from these datasets, though, Heshmati & Kim created a new binary variable corresponding to whether a country was democratic. They assigned a score of 1 to each country that both received a “free” or “partially free” rating in the Freedom House dataset, as well as had a positive Polity IV score, and a 0 to every other country. Naturally, 1 represents a democratic country, while 0 represents a non-democratic country. This allowed them to fill in missing observations for years during which one of the datasets did not have any recorded value. Heshmati & Kim analyzed this data for 144 countries between the years 1980 and 2014, and additionally controlled for credit guarantee and foreign direct investment (FDI). By applying both single and multiple time trend models to their data, Heshmati & Kim found that democracy has a strong positive impact on GDP.

Drury et al. (2006) indirectly researched the relationship between democracy and GDP per capita by analyzing the link between corruption and democracy. They used a time-series cross-section of 102 countries between the years 1982 and 1997, which contained data from the World Bank's World Development Indicators to measure GDP and data from the International Country Risk Guide as a measure of corruption. Additionally, they controlled for variables like life expectancy, population growth, and government spending in their analysis. After splitting their dataset into two groups—one with countries deemed democratic, and the other with countries considered undemocratic—Drury et al. performed multiple regression on each independently. They found that corruption had no statistically significant effect on the GDP of democratic countries, while corruption did have a large negative effect on the GDP of nondemocratic countries. This led them to conclude that even if there is no direct relationship between democracy and economic prosperity, there at minimum tends to be less corruption in democracies compared to non-democracies, which indirectly boosts GDP.

While the previously cited studies mainly rely on time-series analysis to quantify the impact of democracy on economic growth, this paper instead focuses on a single snapshot of time. This controls for economic shocks that were unrelated, yet might have influenced either variable. This also allows us to easily control for the impact of inflation, since our data is from a single year, rather than attempting to account for constantly fluctuating inflation and exchange rates. Furthermore, in this analysis, we consider multiple control variables not evaluated in other research papers. For example, we include the average inflation rate over the previous ten years, the Gini coefficient, and the unemployment rate in our regression equations. Examining these in conjunction with other more widely analyzed control variables, such as FDI and savings rate, should allow us to gain a more comprehensive understanding of the underlying relationship between the level of democracy and the GDP of a country. Additionally, our analysis will include more recent data than any of the studies discussed above, which should allow us to draw more pointed conclusions.

III. Data

To perform analysis on the relationship between the democracy level and GDP per capita of a country, we use a cross-section of multiple datasets. The primary explanatory variable is the Economist's Intelligence Unit (EIU) Democracy Index score, and the dependent variable of interest is the natural logarithm of GDP per capita. The EIU Democracy Index score is a weighted sum of sixty different indicators that describes how democratic a country is. Scores range from zero to ten, with ten being the most democratic score possible. Countries like Finland and Norway consistently rank towards the top of the list with scores well over nine, while countries like North Korea tend to have scores close to zero. For the purposes of this analysis, we will consider the EIU Democracy Index scores of 139 countries from 2018. A list of countries is included in Appendix A. This measure of democracy was chosen because it gives each country a score on a continuum, rather than a simple ranking like many similar indexes. This ensures that our data is spread out in a meaningful way when we perform regression, instead of giving each country a single rank. In the future, we will refer to this variable as *demindex*.

GDP per capita is a well-defined metric, and for purposes of this analysis, we will use the World Bank's 2018 GDP per Capita Index in current USD data. The unit for GDP per capita does not matter, but for simplicity's sake, we will use USD. Furthermore, we will take the natural logarithm of this value when performing regression, a common practice when analyzing the GDP of nations. This transformation allows us to see a linear relationship between our explanatory and dependent variables, since using pure GDP would likely not result in a linear relationship. In the future, we will refer to this variable as *gdpcap* when we are referencing the raw data or *loggdpcap* when we are talking about the natural logarithm of the data. An initial scatterplot of our data shows a relatively strong correlation between our two variables:

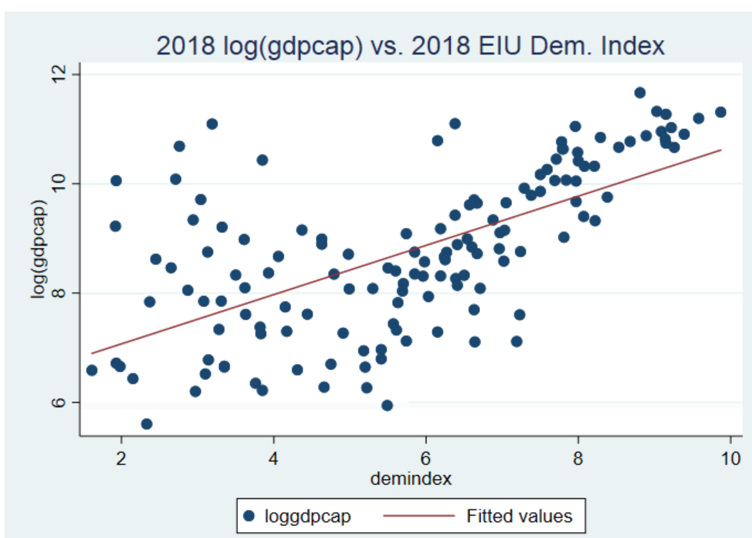

Figure 1

Our first control variable is *avginfl*, the average inflation rate of a country between 2009 and 2019. The raw data for each year during this time period was taken from the World Bank's Consumer Price

Inflation Index, and then averaged using Microsoft Excel. We have chosen to include this in our model because it provides insight into the stability of a nation's economy. Volatile inflation rates could negatively impact a country's GDP, which is why we've decided to control for this. Additionally, we've selected this ten-year time frame because such a duration allows us to analyze the long-term stability of a country, while not looking so far into the past that our data becomes irrelevant.

Our next three control variables are *fdi*, *gini*, and *savings*. As their names suggest, *fdi* is the net inflow of foreign direct investment, *gini* is the Gini coefficient, and *savings* is the savings rate of a country. These three variables are commonly used when analyzing the GDP of countries, and all three were used in Acemoglu et al. and Heshmati & Kim's papers. The net inflow of foreign direct investment can be a good indicator of the strength and stability of an economy, so we would like to control for it. The Gini coefficient ranges from 0 to 100 and is a measure of economic equality, with 100 being a perfectly equal economy. This metric is important for our analysis because it allows us to control for countries' differences in distribution of wealth, but recent data is unfortunately not available for a sizable number of nations. As such, we have decided to take each country's most recent Gini coefficient from the past five years. Finally, we control for the savings rate of a country, since this, too can provide insight into strength and stability of an economy that we would not want to omit. Our last variable is *unemploy*, the unemployment rate of a country in 2018. This variable was not used in any of the previous papers, but is still interesting to include in our analysis to see if it has any underlying relationship with GDP.

A description of each variable can be found in Table 1 below:

Table 1: Variable Descriptions

Variable Name	Description	Units	Source
gdpcap	Gross Domestic Product per capita in 2018	USD	World Bank
loggdpcap	Natural logarithm of Gross Domestic Product per capita in 2018	USD	World Bank
demindex	EIU Democracy Index score in 2018	Points	Economist's Intelligence Unit
avginfl	Average inflation rate between 2009 and 2019	Percentage	World Bank
fdi	Net inflow of foreign direct investment in 2018	Billions USD	World Bank
gini	Most recent Gini coefficient over the past five years	Percentage	World Bank
savings	Savings as a percentage of gross national income in 2018	Percentage	World Bank
unemploy	Unemployment rate in 2018	Percentage	World Bank

Descriptive statistics for each variable can be found in Table 2 below:

Table 2: Descriptive Statistics

Variable Name	Observations	Mean	Std. Dev.	Min	Max
loggdpcap	139	8.78	1.483	5.60	11.67
demindex	139	5.78	2.087	1.61	9.87
avginfl	139	4.63	4.711	-0.03	33.29
fdi	139	8.34	49.908	-361.47	261.48
gini	119	37.74	7.820	24.2	63.00
savings	132	9.16	10.694	-28.37	37.67
unemploy	132	6.66	5.000	0.11	26.91

We now verify the Gauss-Markov assumptions prior to constructing our models.

Assumption 1: Model is linear in parameters. All models that we will construct will be in the form $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ \ldots$ and therefore will satisfy this condition.

Assumption 2: Random sampling. For our analysis, we used data for every country available. Therefore, the random sampling assumption is satisfied.

Assumption 3: No perfect collinearity. As evidenced by the STATA outputs in Appendix C, there is no perfect collinearity between any of the variables.

Assumption 4: Error has zero conditional mean. This assumption is impossible for us to verify and quite tenuous. However, we don't have any evidence that this assumption is false, so we will proceed and interpret results cautiously.

Assumption 5: Homoskedasticity. Similar to assumption four, it is difficult to verify that the values of the explanatory variables don't contain information about the variability of the error. We will again proceed cautiously.

IV. Results

Having addressed the Gauss-Markov assumptions, we can now begin our data analysis. In this section, we will explore three different models to test the hypothesis. The STATA regression outputs for each model can be found in Appendix B, and the STATA correlation calculations for each model can be found in Appendix C.

<u>Model 1:</u>

We start with a simple regression analysis of the relationship between the natural logarithm of GDP per capita and the EIU Democracy Index score of a country. This can be written as:

$$\log(gdpcap) = \beta_0 + \beta_1 demindex + u$$

For this model, we have a sample size of 139 countries. The estimated equation calculated by STATA is:

$$\log(gdpcap) = 6.17 + 0.45 demindex$$

The R-squared of this model is 0.4013 and the correlation coefficient is 0.6335, signifying a relatively strong, positive correlation between the two variables. The estimated value of β_1 is positive and shows that our model predicts a 45% increase in GDP per capita for every one point increase of a country's EIU Democracy Index score.

This model seems to suggest that there exists a positive linear relationship between the EIU Democracy Index score and the GDP per capita of a country. However, there likely exists a large amount of omitted variable bias, since we only performed simple regression and did not control for any other factors. In the following models, we will perform different multiple regression analyses to try to decrease this omitted variable bias and gain a more accurate understanding of the underlying relationship between the two variables of interest.

Model 2:

We next perform multiple regression, including all secondary explanatory variables in our model. The equation for this model is:

$$\log(gdpcap) = \beta_0 + \beta_1 demindex + \beta_2 avginfl + \beta_3 fdi + \beta_4 gini + \beta_5 savings + \beta_6 unemploy + u$$

For this model, we only have a sample size of 119 countries due to the lack of data for *gini*, *savings*, and *unemploy* discussed above. While this is not ideal, our sample size still should be large enough to avoid micronumerosity. The estimated equation calculated by STATA is:

$$\log(gdpcap) = 7.261 + 0.504 demindex - 0.056 avginfl + 0.003 fdi - 0.040 gini + 0.001 savings + 0.021 unemploy$$

The R-squared of this model is 0.7099 and the adjusted R-squared is 0.6944. Notably, the correlation between *demindex* and *loggdpcap* is 0.7966 when controlling for the secondary explanatory variables, which is much higher than in our simple regression model. This suggests that there is a strong positive relationship between these two variables. Furthermore, *demindex* has a p-value of 0.00 and a 95% confidence interval of [0.42, 0.59], showing that it is highly significant. Using a two-sided T-test, *demindex* is significant at the 1% level. The estimated value of β_1 is positive and shows that our model predicts a 50.4% increase in GDP per capita for every one point increase of a country's EIU Democracy Index score, which again is higher than in our simple regression model.

The coefficients of the secondary explanatory variables are not the primary concern of this analysis, but it is interesting to note that our model suggests that *gini* is negatively correlated with *loggdpcap*, while *unemploy* is positively correlated with *loggdpcap*. It does seem plausible that a lower Gini coefficient could be linked to a higher GDP, and the fact that *gini* has a p-value of 0.00—the lowest of all secondary explanatory variables—demonstrates that *gini* is significant even at the 1% level. However, the idea that countries with higher rates of unemployment have higher GDP's does not make much economic sense. Furthermore, the p-value of *unemploy* is quite high at 0.173. This likely means that our analysis could be improved by removing *unemploy* from our regression analysis. Similarly, the p-value of *savings* is very high at 0.894, showing that *savings* might too be an irrelevant variable for this analysis. We will explore these variables further in the following section. All other secondary explanatory variables are statistically significant at the 10% level, with *avginfl* being significant at the 5% level.

Model 3:

To address some of the issues with the previous model discussed above, we will again perform multiple regression, but this time ignore *savings* and *unemploy*. The equation for this model is:

$$\log(gdpcap) = \beta_0 + \beta_1 demindex + \beta_2 avginfl + \beta_3 fdi + \beta_4 gini + u$$

We again only have a sample size of 119 countries for this model, since we are still including *gini* in our analysis. The estimated equation calculated by STATA is:

$$\log(gdpcap) = 7.253 + 0.511 demindex - 0.054 avginfl + 0.003 fdi - 0.037 gini$$

The R-squared of this model is 0.7050, which is marginally lower than in the previous models, but the adjusted R-squared is slightly higher than before at 0.6947. Additionally, the correlation between *demindex* and *loggdpcap* remains 0.7966 when controlling for this smaller subset of secondary explanatory variables. The estimated value of β_1 is positive and shows that our model predicts a 51.1% increase in GDP per capita for every one point increase of a country's EIU Democracy Index score, which is also slightly higher than before. The coefficients of the secondary explanatory variables for this model all seem to make economic sense. All variables are significant at the 1% level, except for *fdi*, which is still significant at the 10% level.

The table below shows a summary of the four regression models explored previously, where the numbers in parentheses below the estimates are the standard errors of each value.

	Dependent Variable: log(gdpcap)		
Independent Variables	Model 1	Model 2	Model 3
demindex	0.450*** (0.05)	0.505*** (0.04)	0.511*** (0.04)
avginfl	-	– 0.057** (0.02)	– 0.054*** (0.02)
fdi	-	0.003* (0.001)	0.003* (0.001)
gini	-	– 0.040*** (0.10)	– 0.037*** (0.01)
savings	-	0.001 (0.01)	-
unemploy	-	0.021 (0.02)	-
constant	6.172*** (0.29)	7.261*** (0.53)	7.253*** (0.52)
No. Observations	139	119	119
R-squared	0.4013	0.7099	0.7050
Adj. R-squared	0.3969	0.6944	0.6947

*Significant at 10%, **5%, ***1%

V. Extensions

In our analysis of Model 2, we saw that *savings* and *unemploy* were individually insignificant variables using a two-sided T-test. However, we haven't yet determined that they are jointly insignificant. To do so, we will conduct a joint F-Test on *savings* and *unemploy* in Model 2, using Model 3 as our restricted model. The following are our hypotheses for this F-Test:

$$H_0: \beta_5 = 0, \beta_6 = 0$$

$$H_1: H_0 \ is \ false$$

Using the R-squared value for both the restricted and unrestricted models, we calculate the F-value of this test to be 0.084. At the 10% level, the critical value $F_{2,\,112} \approx F_{2,\,120}$ is 2.35. Because the critical value of the F-distribution is greater than the F-value we found, at the 10% significance level, we fail to reject the null hypothesis and conclude *savings* and *unemploy* are jointly insignificant. Because of this, we take Model 3 as our more accurate model. We now consider another possible model.

<u>Model 4:</u>

Even though the p-value of *savings* was very high in Model 2, it would make economic sense for there to be a direct relationship between *loggdpcap* and *savings*. Therefore, we will try a different model using both *savings* and *(savings)*^{2} to see if a misrepresentation of the underlying relationship between *loggdpcap* and *savings* is causing the statistical insignificance. In this model, we will drop *unemploy* and instead focus on the significance of *savings* and *(savings)*^{2}. The equation for this model is:

$$\log(gdpcap) \ = \ \beta_0 \ + \ \beta_1 demindex + \beta_2 avginfl + \beta_3 fdi + \beta_4 gini + \beta_5 savings + \beta_6 savings^2 + u$$

We still have a sample size of 119 countries for this model, since we include *gini* in our analysis. The estimated equation calculated by STATA is:

$$\log(gdpcap) \ = \ 3.126 \ + \ 0.225 demindex - 0.023 avginfl + 0.001 fdi - 0.016 gini - 0.002 savings + 0.0001 savings^2$$

The R-squared of this model is 0.7062 and the adjusted R-squared is 0.6905, which are both lower than in the Model 2. Nevertheless, the correlation between *demindex* and *loggdpcap* remains 0.7966. Additionally, the estimated value of β_1 is positive and shows that our model predicts a 22.5% increase in GDP per capita for every one point increase of a country's EIU Democracy Index score, which is almost half as much as before. However, the main variables of interest in this model are *savings* and *(savings)*^{2}. The former has a p-value of 0.673 and a 95% confidence interval of [-0.0098, 0.0063], while the latter has a p-value of 0.501 and a 95% confidence interval of [-0.0002, 0.0005].

Clearly, neither is statistically significant using a two-sided test at even the 10% level. This demonstrates that *savings* is still not a very useful control variable when we include its square in our regression model.

VI. Conclusions

Each linear regression model we considered in this study supported our initial hypothesis that there exists a positive correlation between the EIU Democracy Index level and GDP per capita of a country. In our first model, we observed an R-squared value of 0.4, which highlights the mild apparent relationship between the two. However, in our second third, and fourth models, we saw an R-squared value of nearly 0.7, demonstrating that there is in fact a much stronger relationship when we control for external variables. Therefore, it seems reasonable to conclude that more democratic countries tend to also have higher GDP's per capita, all else being equal.

Analyzing our secondary explanatory variables, we determined that a country's average inflation rate, net inflow of foreign direct investment, and Gini coefficient do have a substantial impact on GDP per capita across every model we studied. According to our models, higher average inflation rates and higher Gini coefficients tend to decrease a country's GDP per capita, all else being equal, while higher net inflows of foreign direct investment tend to increase this value. On the other hand, a nation's savings and unemployment rates do not seem to have a significant influence. This is a somewhat surprising conclusion, and one that may warrant further research. Moreover, it is highly likely that additional control variables could improve the accuracy of our models. With this in mind, future studies could explore other factors that might influence GDP per capita in order to build upon our work. Nevertheless, we still are able to say with high confidence that there exists a strong positive relationship between the democracy level of a country and its GDP per capita.

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Appendix A: List of Countries Used in Study

Afghanistan	Colombia	Honduras	Mali	Romania
Angola	Costa Rica	Croatia	Malta	Russian Federation
Albania	Cyprus	Haiti	Myanmar	Rwanda
United Arab Emirates	Czech Republic	Hungary	Montenegro	Saudi Arabia
Armenia	Germany	Indonesia	Mongolia	Sudan
Australia	Djibouti	India	Mozambique	Senegal
Austria	Denmark	Ireland	Mauritania	Singapore
Azerbaijan	Dominican Republic	Iran, Islamic Rep.	Mauritius	Sierra Leone
Burundi	Algeria	Iraq	Malawi	El Salvador
Belgium	Ecuador	Iceland	Malaysia	Serbia
Benin	Spain	Israel	Namibia	Slovenia
Burkina Faso	Estonia	Italy	Niger	Sweden
Bangladesh	Ethiopia	Jamaica	Nigeria	Chad
Bulgaria	Finland	Jordan	Nicaragua	Togo
Bahrain	Fiji	Japan	Netherlands	Thailand
Bosnia and Herzegovina	France	Korea, Rep.	Norway	Tajikistan
Belarus	Gabon	Kuwait	Nepal	Timor-Leste
Bolivia	United Kingdom	Lao PDR	New Zealand	Tunisia
Brazil	Georgia	Lebanon	Oman	Turkey
Bhutan	Ghana	Sri Lanka	Pakistan	Tanzania
Botswana	Guinea	Lesotho	Panama	Uganda
Canada	Gambia, The	Lithuania	Peru	Ukraine
Switzerland	Guinea-Bissau	Luxembourg	Philippines	Uruguay
Chile	Equatorial Guinea	Latvia	Papua New Guinea	United States
China	Greece	Morocco	Poland	Vietnam
Cote d'Ivoire	Guatemala	Moldova	Portugal	South Africa
Cameroon	Guyana	Madagascar	Paraguay	Zambia
Congo, Rep.	Hong Kong SAR, China	Mexico	Qatar	

Appendix B: STATA Regression Model Outputs

Model 1:

```
. regress loggdpcap demindex

      Source |       SS           df       MS      Number of obs   =       139
-------------+----------------------------------   F(1, 137)       =     91.82
       Model |  121.820239         1  121.820239   Prob > F        =    0.0000
    Residual |   181.76123       137  1.32672431   R-squared       =    0.4013
-------------+----------------------------------   Adj R-squared   =    0.3969
       Total |  303.581469       138  2.19986572   Root MSE        =    1.1518

------------------------------------------------------------------------------
   loggdpcap |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    demindex |   .4502746   .0469903     9.58   0.000     .3573546    .5431947
       _cons |   6.172438   .2886693    21.38   0.000     5.601614    6.743262
------------------------------------------------------------------------------
```

Model 2:

```
. regress loggdpcap demindex avginfl fdi gini savings unemploy

      Source |       SS           df       MS      Number of obs   =       119
-------------+----------------------------------   F(6, 112)       =     45.69
       Model |  182.830057         6  30.4716761   Prob > F        =    0.0000
    Residual |  74.7026464       112  .666987915   R-squared       =    0.7099
-------------+----------------------------------   Adj R-squared   =    0.6944
       Total |  257.532703       118  2.18248053   Root MSE        =    .81669

------------------------------------------------------------------------------
   loggdpcap |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    demindex |   .5044747    .042714    11.81   0.000     .4198423     .589107
     avginfl |  -.0565046   .0174666    -3.24   0.002    -.0911125   -.0218968
         fdi |   .0027265   .0014365     1.90   0.060    -.0001198    .0055727
        gini |  -.0398044   .0101666    -3.92   0.000    -.0599482   -.0196607
     savings |   .0010222    .007621     0.13   0.894    -.0140778    .0161222
    unemploy |   .0211039   .0153718     1.37   0.173    -.0093534    .0515612
       _cons |    7.26145   .5269965    13.78   0.000     6.217274    8.305627
------------------------------------------------------------------------------
```

Model 3:

```
. regress loggdpcap demindex avginfl fdi gini
```

Source	SS	df	MS
Model	181.571946	4	45.3929865
Residual	75.9607571	114	.666322431
Total	257.532703	118	2.18248053

Number of obs	=	119
F(4, 114)	=	68.12
Prob > F	=	0.0000
R-squared	=	0.7050
Adj R-squared	=	0.6947
Root MSE	=	.81629

loggdpcap	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
demindex	.5110853	.0424074	12.05	0.000	.4270766	.595094
avginfl	-.0541157	.0173596	-3.12	0.002	-.0885049	-.0197265
fdi	.0026726	.0014351	1.86	0.065	-.0001702	.0055155
gini	-.0368942	.0098874	-3.73	0.000	-.056481	-.0173074
_cons	7.252704	.5148074	14.09	0.000	6.232875	8.272534

Model 4:

```
. regress loggdpcap demindex avginfl fdi gini savings savingssq
```

Source	SS	df	MS
Model	34.3048866	6	5.7174811
Residual	14.2687958	112	.127399963
Total	48.5736824	118	.411641377

Number of obs	=	119
F(6, 112)	=	44.88
Prob > F	=	0.0000
R-squared	=	0.7062
Adj R-squared	=	0.6905
Root MSE	=	.35693

loggdpcap	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
demindex	.2254807	.0192763	11.70	0.000	.1872872	.2636742
avginfl	-.0234346	.0075974	-3.08	0.003	-.0384879	-.0083813
fdi	.0011667	.0006277	1.86	0.066	-.0000769	.0024103
gini	-.0161326	.0043504	-3.71	0.000	-.0247524	-.0075128
savings	-.0017229	.0040657	-0.42	0.673	-.0097785	.0063327
savingssq	.0001212	.0001795	0.68	0.501	-.0002344	.0004768
_cons	3.126314	.233346	13.40	0.000	2.663969	3.588659

Appendix C: STATA Correlation Outputs

Model 1:

```
. correlate loggdpcap demindex
(obs=139)
```

	loggdp~p	demindex
loggdpcap	1.0000	
demindex	0.6335	1.0000

Model 2:

```
. correlate loggdpcap demindex avginfl fdi gini savings unemploy
(obs=119)
```

	loggdp~p	demindex	avginfl	fdi	gini	savings	unemploy
loggdpcap	1.0000						
demindex	0.7966	1.0000					
avginfl	-0.4827	-0.4118	1.0000				
fdi	0.0855	0.0028	-0.0466	1.0000			
gini	-0.3484	-0.2090	0.1141	0.1020	1.0000		
savings	0.0308	0.0092	-0.0417	-0.0249	-0.1098	1.0000	
unemploy	0.0340	0.0329	0.0852	-0.0070	0.2066	-0.1475	1.0000

Model 3:

```
. correlate loggdpcap demindex avginfl fdi gini
(obs=119)
```

	loggdp~p	demindex	avginfl	fdi	gini
loggdpcap	1.0000				
demindex	0.7966	1.0000			
avginfl	-0.4827	-0.4118	1.0000		
fdi	0.0855	0.0028	-0.0466	1.0000	
gini	-0.3484	-0.2090	0.1141	0.1020	1.0000

Model 4:

```
. correlate loggdpcap demindex avginfl fdi gini savings savingssq
(obs=119)
```

	loggdp~p	demindex	avginfl	fdi	gini	savings	saving~q
loggdpcap	1.0000						
demindex	0.7966	1.0000					
avginfl	-0.4827	-0.4118	1.0000				
fdi	0.0855	0.0028	-0.0466	1.0000			
gini	-0.3484	-0.2090	0.1141	0.1020	1.0000		
savings	0.0308	0.0092	-0.0417	-0.0249	-0.1098	1.0000	
savingssq	-0.1565	-0.2428	0.0687	-0.0235	0.0124	0.5639	1.0000